

A Digital Twin-Based Simulation and Intelligent Network Operations Framework for 6G Networks

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Abstract: The rapid evolution of sixth-generation (6G) wireless networks is expected to introduce highly heterogeneous network infrastructures, dynamic traffic conditions, stringent latency requirements, and increased demands for reliability, scalability, and intelligent network management. These characteristics make conventional network management approaches insufficient for evaluating complex network behavior under changing traffic, mobility, resource utilization, and failure conditions. This paper presents a digital twin-based simulation and intelligent network operations framework for 6G networks that provides an integrated environment for modeling, monitoring, analyzing, and optimizing network operations. The proposed framework represents heterogeneous network nodes, communication links, traffic flows, network slices, mobility conditions, propagation characteristics, and resource states using a structured simulation model. A capacity-aware routing mechanism is employed to determine feasible paths while supporting flow rerouting when network resources become unavailable or degraded. The framework further incorporates network slicing for differentiated traffic classes, mobility and handover modeling, propagation delay and free-space path-loss estimation, failure injection and recovery, and immutable digital twin snapshots for maintaining consistent representations of network states. Network analytics are used to evaluate key performance indicators including availability, flow success rate, utilization, throughput, latency, bandwidth, active flows, and energy consumption. An explainable optimization module analyzes these metrics and generates rule-based recommendations for congestion reduction, latency improvement, energy efficiency, and network recovery. The framework is implemented as a self-contained simulation environment with a graphical network operations interface, enabling controlled and reproducible experimentation using deterministic synthetic telemetry. The proposed approach provides a unified platform for studying 6G network behavior and demonstrates how digital twin modeling, simulation-driven analytics, failure-aware routing, and intelligent operational recommendations can support more reliable and adaptive network management.

Keywords: 6G Networks, Digital Twin, Network Simulation, Intelligent Network Operations, Capacity-Aware Routing,

Network Slicing, Mobility Management, Failure Recovery, Network Analytics, Explainable Optimization.

I. INTRODUCTION

The rapid advancement of wireless communication technologies has increased the demand for network infrastructures capable of supporting high data rates, ultra-low latency, massive device connectivity, and reliable communication. While fifth-generation (5G) networks have introduced significant improvements in mobile communication, the anticipated requirements of sixth-generation (6G) networks extend beyond conventional connectivity to include intelligent automation, heterogeneous network integration, dynamic resource management, and enhanced service reliability. Future 6G environments are expected to involve diverse network components, including terrestrial base stations, satellites, unmanned aerial vehicles, edge computing nodes, Internet of Things (IoT) devices, and high-capacity communication links. Managing these interconnected components presents considerable challenges because network performance can change continuously in response to traffic demand, mobility, congestion, link degradation, and resource failures. Traditional network management approaches often depend on monitoring individual network components or evaluating specific performance parameters independently. Although these methods provide useful operational information, they may not adequately represent the interactions between network topology, traffic flows, resource availability, mobility, and failure conditions. For example, a communication link failure can affect multiple traffic flows, increase latency, reduce throughput, and require alternative routing paths. Similarly, excessive resource utilization may result in congestion and reduced service quality. These interconnected effects highlight the need for an integrated environment in which network behavior can be simulated, monitored, and analyzed under controlled operating conditions. Digital twin technology provides a promising approach to addressing these challenges by maintaining a digital representation of network components, resource states, and operational conditions. When combined with simulation and network analytics, a digital twin can support the

observation of network behavior, evaluation of alternative operating conditions, and identification of potential performance issues. In a 6G network environment, such a framework can help analyze the consequences of traffic variations, mobility events, resource failures, and routing decisions without requiring a continuously operating physical network testbed. However, the practical usefulness of a digital twin depends on its ability to represent relevant network characteristics and connect simulation results with meaningful operational decisions. This paper presents a digital twin-based simulation and intelligent network operations framework designed for modeling and analyzing 6G network behavior. The framework incorporates heterogeneous network topology, typed node and link resources, traffic-flow management, capacity-aware routing, network slicing, mobility modeling, propagation calculations, and failure and recovery operations. Its routing mechanism uses a capacity-aware shortest-path approach to identify feasible communication paths and supports rerouting when network conditions change. The framework also maintains digital twin snapshots that provide consistent representations of simulation states, enabling network conditions to be examined and recorded systematically. To support performance evaluation, the framework calculates key network indicators, including node and link availability, flow success rate, network utilization, throughput, latency, bandwidth, active flows, and energy consumption. These metrics are analyzed by a rule-based optimization module that generates operational recommendations according to observed network conditions. For instance, high utilization can trigger recommendations related to capacity expansion or traffic rerouting, while elevated latency can indicate the need for lower-latency paths. The framework also provides a graphical network operations interface for monitoring network status, visualizing performance trends, observing alarms, and examining simulated network events. The implementation operates as a self-contained simulation environment using deterministic synthetic telemetry, allowing experiments to be conducted under reproducible conditions without requiring external cloud services or live network data. By integrating network simulation, digital twin state management, performance analytics, failure-aware routing, and explainable operational recommendations, the proposed framework provides a practical platform for investigating network behavior and management strategies relevant to emerging 6G environments. The work focuses on simulation-based evaluation and operational decision support rather than claiming validation on a deployed physical 6G network. The remainder of this paper reviews related research and existing approaches to 6G network management, identifies the problem and research gap, describes the proposed framework and its operational workflow, and presents the mathematical models, implementation details, evaluation methodology, and potential directions for future development.

CONTRIBUTIONS

The major contributions of this paper are summarized as follows:

1. **Integrated Digital Twin-Based 6G Simulation Framework:** A unified simulation framework is developed to represent heterogeneous 6G network components,

communication links, traffic flows, and resource states within a common operational environment.

2. **Capacity-Aware Routing and Rerouting:** A capacity-aware shortest-path routing mechanism is incorporated to identify feasible communication paths based on link latency and available capacity. The framework also supports rerouting when network failures or resource changes affect existing traffic flows.
3. **Network Slicing and Mobility Modeling:** The framework integrates differentiated traffic classes, including Ultra-Reliable Low-Latency Communications (URLLC), enhanced Mobile Broadband (eMBB), and massive Machine-Type Communications (mMTC). Mobility and handover behavior are also represented to examine their effects on network operations.
4. **Failure and Recovery Management:** Network failure injection and recovery mechanisms are incorporated to investigate the effects of unavailable nodes and links on connectivity, routing, and service continuity.
5. **Comprehensive Network Performance Analytics:** The framework evaluates important performance indicators, including node and link availability, flow success rate, network utilization, throughput, latency, bandwidth, active flows, and energy consumption, providing a structured basis for examining simulated network conditions.
6. **Digital Twin Snapshot Management:** Immutable digital twin snapshots and JSON serialization are incorporated to preserve consistent representations of simulation states, supporting network-state inspection, reporting, and reproducible analysis.
7. **Explainable Operational Optimization:** A rule-based optimization module analyzes network performance indicators and produces interpretable recommendations for addressing congestion, reducing latency, improving energy efficiency, and recovering failed resources.
8. **Interactive Network Operations Interface:** A graphical Network Operations Center (NOC) interface integrates network visualization, performance monitoring, analytics, alarms, and operational controls, providing a practical environment for observing and managing simulated network scenarios.
9. Together, these contributions establish a simulation-oriented platform for investigating 6G network behavior by combining digital twin modeling, capacity-aware routing, network slicing, failure management, performance analytics, and explainable operational recommendations within a single framework.

II. LITERATURE REVIEW

A. 6G Network Architecture and Heterogeneous Infrastructure

The development of sixth-generation (6G) wireless communication has attracted considerable research attention because of the anticipated requirements for high data rates, ultra-low latency, massive connectivity, and intelligent network operation. Unlike conventional cellular networks, future 6G infrastructures are expected to integrate terrestrial

communication systems with satellite networks, aerial platforms, edge computing facilities, and large numbers of connected devices. These heterogeneous components introduce additional complexity in network topology management, resource allocation, mobility support, and end-to-end service delivery. Akbar et al. examined the requirements, applications, and security challenges associated with 6G networks, highlighting the diverse technical considerations involved in realizing future communication systems [1]. Such developments emphasize the importance of flexible network models that can represent different node types, communication links, resource capacities, and operational conditions. For simulation-based research, a structured representation of these components provides a foundation for analyzing network performance under different configurations.

B. Digital Twin-Based Network Management

Digital twin technology has emerged as a promising approach for representing and analyzing complex communication systems through corresponding digital models. A network digital twin can combine network topology, resource information, operational states, and performance measurements to support monitoring, simulation, and decision-making. Khan et al. discussed the potential of digital twins in 6G systems, including their architectural requirements and applications in future network services [2]. Their work illustrates the importance of integrating digital representations with communication and computing capabilities to support intelligent network operation. More recently, research on network digital twin architectures has examined the integration of simulation, artificial intelligence, and network management functions, while identifying challenges associated with accurate modeling, interoperability, and operational integration [3]. These studies establish digital twins as an important research direction for future networks. However, developing a practical framework also requires suitable mechanisms for representing network states, recording changes, evaluating performance, and translating simulation outcomes into understandable operational recommendations.

C. Traffic Routing and Resource Allocation

Routing and resource allocation are fundamental aspects of communication network management because they determine how traffic is transmitted through available network resources. Conventional shortest-path algorithms select routes according to a predefined path cost, such as distance, hop count, or latency. However, in heterogeneous networks, a path with low latency may not be suitable when its available bandwidth is insufficient for the requested traffic demand. Capacity-aware routing therefore considers resource constraints alongside path cost when identifying feasible communication routes. In a dynamic network environment, failures and changes in link availability may also require existing traffic flows to be redirected through alternative paths. These requirements become particularly relevant when evaluating network congestion, throughput, and service continuity. The proposed framework incorporates a capacity-aware Dijkstra-based routing mechanism that evaluates link latency while excluding links that cannot accommodate the required traffic demand. This approach provides a practical basis for studying feasible path selection and rerouting within a

controlled simulation environment. Nevertheless, its performance must be evaluated against suitable routing alternatives before conclusions about comparative superiority can be established.

D. Network Slicing and Differentiated Traffic Management

Network slicing enables a shared communication infrastructure to support multiple logical network environments with different service requirements. Research on network slicing and software-defined networking has examined the principles, enabling technologies, orchestration mechanisms, and challenges involved in allocating network resources to different services [4]. This approach is relevant to 6G because emerging applications may impose substantially different requirements on latency, bandwidth, reliability, and device connectivity. For example, Ultra-Reliable Low-Latency Communications (URLLC) focuses on demanding latency and reliability requirements, enhanced Mobile Broadband (eMBB) supports high-throughput applications, and massive Machine-Type Communications (mMTC) addresses large-scale device connectivity. Managing these traffic categories requires mechanisms for representing service classes and tracking resource allocation. The proposed framework incorporates these three traffic classes and supports slice-related admission and bandwidth accounting. This allows differentiated traffic demands to be represented in simulation. However, the presence of traffic classes alone does not establish full end-to-end network slicing, which would require additional orchestration and isolation mechanisms beyond the current implementation.

E. Mobility and Handover Management

Mobility management is an important consideration in future wireless networks because mobile users, connected vehicles, and aerial devices may change their positions and communication access points during operation. Such changes can influence connectivity, propagation distance, signal conditions, and the selection of an appropriate access node. Handover mechanisms are intended to maintain communication continuity as devices move between serving access points. In heterogeneous 6G environments, mobility may involve different types of terrestrial and non-terrestrial infrastructure, making access-point selection more complex. A simulation framework can help investigate these conditions by representing node positions, movement velocities, access-point availability, and handover events. The proposed framework incorporates mobility-state modeling and access-point selection based on proximity to active gNB or satellite nodes. This provides a foundation for studying changes in connectivity under simulated movement. Nevertheless, detailed radio-resource control, interference-aware handover decisions, and real-world mobility traces would require further modeling and validation.

F. Failure Management and Network Resilience

Network resilience refers to the ability of a communication system to maintain or restore service when components become unavailable or experience degraded performance. Node failures, link interruptions, congestion, and resource limitations can disrupt communication paths and reduce overall network availability. These problems are particularly important in

heterogeneous networks because individual failures may affect multiple interconnected flows. Failure-aware routing and recovery mechanisms can reduce disruption by identifying alternative paths or restoring unavailable resources. Simulation-based fault injection provides a controlled way to examine how networks respond to such events without affecting operational infrastructure. The proposed framework supports failure and recovery operations, flow rerouting, and the recording of network events. It also evaluates availability and flow success rate to help characterize the effects of changing network conditions. This integration enables systematic examination of failure scenarios and recovery behavior, although actual resilience performance must be established through experiments involving defined failure patterns, recovery times, and comparison baselines.

G. Propagation and Communication Link Modeling

Accurate representation of communication links is necessary for studying the performance of heterogeneous wireless networks. Link behavior may depend on transmission distance, carrier frequency, propagation conditions, latency, available capacity, packet loss, jitter, and congestion. At higher frequencies, including millimeter-wave and terahertz bands considered for future communication systems, propagation characteristics can become especially important to link feasibility and network planning. Free-space path loss provides a basic theoretical model for estimating signal attenuation under idealized propagation conditions, while propagation delay can be estimated from distance and propagation velocity. However, free-space models do not fully capture environmental obstruction, multipath fading, atmospheric absorption, interference, or other real-world effects. The proposed framework includes propagation calculations for free-space path loss and propagation delay, together with typed link metadata for capacity, latency, reliability, and other performance characteristics. These mechanisms support controlled link-level analysis, while more detailed channel models would be necessary for realistic radio-frequency performance studies.

H. Intelligent Network Optimization and Performance Analytics

Intelligent network management aims to improve operational efficiency by using performance measurements to identify problems and guide resource-management decisions. Research into intent-driven and intelligent networking has explored ways to reduce operational complexity through automated interpretation of network objectives and coordinated management functions [5]. In a simulation environment, performance analytics can provide the information required to detect congestion, identify excessive latency, monitor resource availability, and assess energy consumption. Optimization techniques can then use these measurements to recommend actions such as rerouting traffic, increasing capacity, or recovering failed resources. The proposed framework calculates network indicators including node and link availability, flow success rate, utilization, throughput, latency, bandwidth, active flows, and energy consumption. A rule-based optimization module interprets selected metrics and generates recommendations according to predefined thresholds. This design provides understandable explanations for suggested

operational actions without requiring a trained machine-learning model. However, these recommendations should be distinguished from automatically validated optimal decisions, as their effectiveness depends on the chosen rules, thresholds, network configuration, and experimental conditions.

I. Comparative Perspective and Summary of Existing Approaches

The reviewed literature demonstrates that 6G network management involves several closely related research areas, including heterogeneous infrastructure modelling, digital twins, routing, network slicing, mobility management, resilience, propagation analysis, and intelligent optimization. Existing studies provide important foundations for understanding these individual areas and their relevance to future communication systems. Nevertheless, an integrated simulation environment must coordinate these functions so that changes in one component can be examined in relation to other network conditions. For example, a link failure can influence route availability, traffic delivery, utilization, latency, and overall network performance. Similarly, mobility events may change access-point selection and affect connectivity. Evaluating these interactions requires more than isolated performance calculations.

The framework presented in this paper brings together heterogeneous topology modelling, capacity-aware routing, differentiated traffic classes, mobility representation, propagation calculations, failure and recovery operations, network analytics, digital twin snapshots, and rule-based operational recommendations. Its primary contribution is the integration of these functions into a self-contained and reproducible simulation environment with a graphical network operations interface. Unlike approaches that focus on a single network-management function, the framework is designed to support coordinated examination of network states and operational scenarios. Its current implementation uses deterministic synthetic telemetry and simulation models; therefore, its results should be interpreted as simulation-based findings rather than direct evidence of performance in a deployed 6G network. This integrated design provides the basis for the problem statement, research gap, and methodology discussed in the following sections.

III. EXTENDED RELATED WORK BY ARCHITECTURE FAMILY

IV. Heterogeneous 6G Network Architectures

Heterogeneous network architectures are an important foundation of sixth-generation communication systems because they enable the integration of different communication technologies, access networks, and computing resources. Recent architectural studies have examined the potential combination of terrestrial infrastructure, non-terrestrial networks, intelligent radio technologies, and AI-assisted resource management to support diverse 6G applications [6]. These architectures introduce flexibility but also increase the complexity of topology management, routing, resource allocation, and network coordination. The interaction between different node types and communication links must be considered when evaluating network performance. The proposed framework addresses this

requirement by 5G modelling heterogeneous node categories, including base stations, edge and mobile computing resources, satellites, aerial platforms, IoT devices, and user equipment. Communication links are represented with associated capacities, latency, reliability, and other resource characteristics. This structured 5G modelling approach supports the simulation of heterogeneous network configurations, although it does not represent a complete standards-compliant 6G protocol stack.

B. Digital Twin-Based Network Architectures

Digital twin-based network architectures provide a virtual representation of network infrastructure for observing operational states, simulating alternative scenarios, and supporting network management decisions. Existing research has examined network digital twin architecture, model construction, synchronization, and integration with intelligent management systems [7]. More recent work has proposed native digital twin architectures for 6G networks, emphasizing model construction, operational-state representation, and intelligent orchestration [8]. These approaches demonstrate the potential of digital twins to support network analysis and pre-deployment evaluation. However, the fidelity and usefulness of a digital twin depend on its underlying models, the quality of its input data, and its ability to represent changes in network conditions. The proposed framework implements a simulation-oriented digital twin model that maintains network entities and creates immutable snapshots of simulation states. JSON serialization supports the inspection and recording of these states. Unlike a production network digital twin connected to live infrastructure, the current implementation operates with deterministic synthetic telemetry and does not claim real-time synchronization with a physical 6G network.

C. Routing and Traffic Management Architectures

Routing architectures determine how traffic flows are assigned to paths through a network, while traffic management mechanisms coordinate the use of available resources. Conventional shortest-path routing provides a computationally practical method for selecting paths according to a defined link cost. However, latency alone may not be sufficient when links have different capacities or when traffic demand changes dynamically. Capacity-aware routing incorporates resource feasibility into path selection, helping avoid routes that cannot accommodate a requested flow. Research on future network architectures continues to identify efficient resource allocation and adaptive network control as important challenges for 6G systems [6]. The proposed framework uses a Dijkstra-based routing algorithm that considers link latency while excluding links with insufficient residual capacity for the requested demand. Traffic-flow management maintains route allocation and supports rerouting when network conditions change. This design provides a basis for studying path feasibility and traffic continuity, although its effectiveness relative to other routing algorithms requires systematic experimental comparison.

D. Network Slicing and Service-Oriented Architectures

Network slicing enables a shared network infrastructure to support different categories of service through logically differentiated resource allocation. Research on network slicing and softwarization has explored resource management, service

customization, and orchestration across access, transport, and core network components [9]. These principles are relevant to 6G environments in which applications may require different combinations of throughput, latency, reliability, and connectivity. A simulation framework can use traffic classes to represent these distinct service demands and examine their relationship with resource availability. The proposed implementation includes URLLC, EMBB, and mMTC traffic classes, together with slice admission and bandwidth accounting. This functionality supports simulation-based analysis of differentiated traffic allocation. However, the implementation should be understood as a slice-related resource-management model rather than a complete end-to-end slicing architecture, since comprehensive slice orchestration, isolation, and service-level enforcement are not fully implemented.

E. Mobility-Aware and Heterogeneous Access Architectures

Mobility-aware network architectures are designed to maintain connectivity as users and devices move through changing coverage areas. In heterogeneous environments, mobility management may involve transitions between terrestrial base stations, aerial access points, and satellite connectivity. Access-point selection can influence communication distance, propagation delay, and the availability of alternative routes. The complexity of integrating different access technologies is also recognized in recent 6G architecture studies [6]. Simulation-based mobility modelling allows researchers to examine changes in node positions and access-point availability without requiring physical devices to move through real environments. The proposed framework represents mobility states through position and velocity information and supports access-point selection based on proximity to active GNB or satellite nodes. Handover-related events can be used to observe changes in simulated connectivity. Nevertheless, the current model does not constitute a full radio mobility-management protocol, and aspects such as interference-aware handover decisions, radio measurements, and detailed cellular signaling remain outside its present scope.

F. Propagation-Aware Communication Architectures

Propagation modelling is necessary for understanding how distance and transmission frequency influence communication links. This becomes increasingly relevant for future networks considering millimeter-wave and terahertz communications, where propagation conditions may significantly affect link feasibility. Digital twin research for 6G has also explored the representation of wireless channels and the potential use of channel twins to improve communication-system analysis [10]. Detailed propagation models can incorporate environmental conditions, obstacles, fading, and other radio-frequency effects, but these models may require additional data and computational resources. The proposed framework includes free-space path-loss estimation and propagation-delay calculation, alongside link properties such as latency, capacity, reliability, jitter, and signal quality. These features provide a basic representation of communication-link behavior for network-level experiments. However, free-space path loss is an idealized model and should not be interpreted as a comprehensive prediction of real-world wireless channel performance.

G. Failure-Aware and Resilient Network Architectures

Network resilience depends on the ability to identify failures, preserve connectivity where possible, and restore service when network resources become unavailable. Failure-aware architectures examine how disruptions to nodes or communication links influence network reachability and the performance of active traffic flows. Digital twin-based approaches are particularly relevant because failure scenarios can be reproduced in a controlled environment before corresponding changes are considered in a physical network [7], [8]. The proposed framework incorporates failure and recovery operations, routing updates, and flow rerouting to examine how the network responds to changing resource availability. Performance indicators such as node availability, link availability, overall availability, and flow success rate provide a quantitative basis for evaluating these scenarios. This functionality supports controlled resilience experiments, but it does not by itself demonstrate fault tolerance under real operational conditions. Such claims would require experiments with defined failure distributions, recovery procedures, and comparative baselines.

H. Analytics-Driven and Explainable Optimization Architectures

Intelligent network optimization uses operational measurements to identify performance issues and guide resource-management decisions. Research on digital twin networks has investigated the integration of analytics, AI techniques, and optimization mechanisms to improve network monitoring and management [7], [11]. Learning-based approaches may support complex prediction and decision-making tasks, but they can require substantial training data, computational resources, and validation. Rule-based methods provide a simpler alternative when the objective is to produce transparent recommendations from defined performance thresholds. The proposed framework follows this approach by analyzing network utilization, latency, energy consumption relative to throughput, and availability. For example, high utilization can lead to recommendations for capacity expansion or rerouting, while elevated latency can lead to recommendations for recovering failed resources. The recommendations are interpretable because they are linked to explicit rules and observed metrics. However, the current optimization module provides rule-based operational guidance rather than a learned AI optimizer or a guarantee of globally optimal network performance.

IV. COMPARATIVE DISCUSSION

The reviewed architecture families address complementary aspects of future network operation. Heterogeneous network models provide the structural representation of nodes and communication links, while routing and traffic-management mechanisms determine how flows use available resources. Network slicing supports differentiated traffic classes, mobility modelling represents changes in connectivity, and propagation models estimate selected link characteristics. Failure-management mechanisms help examine disruptions, whereas digital twin snapshots and analytics provide a consistent basis for

observing simulation states and evaluating performance. Intelligent optimization can then translate selected metrics into operational recommendations.

The principal distinction of the proposed framework is its integration of these functions within a single, self-contained simulation environment with a graphical Network Operations Center interface. Rather than concentrating exclusively on one architecture family, it combines topology management, capacity-aware routing, slicing, mobility, propagation calculations, failure recovery, performance analytics, digital twin snapshot generation, and rule-based optimization. This integration supports coordinated investigation of network events and their effects on multiple performance indicators. At the same time, the framework remains a simulation platform based on deterministic synthetic telemetry. Its current capabilities should therefore be distinguished from production-grade digital twins that synchronize with physical networks, advanced AI-based autonomous controllers, and fully implemented 6G protocol architectures. These distinctions establish the scope within which the proposed framework can be evaluated and provide the basis for the problem statement and research gap developed in the following sections.

IV. DEEP LEARNING VERSUS TRADITIONAL MACHINE LEARNING

Traditional machine learning and deep learning represent two different approaches to data analysis and intelligent decision-making. Traditional machine learning techniques generally depend on predefined features, mathematical models, and algorithms to identify patterns in data. In communication networks, these techniques can be applied to traffic classification, anomaly detection, resource allocation, performance prediction, and network optimization. Algorithms such as decision trees, support vector machines, random forests, and gradient-boosting methods can process network measurements, including latency, throughput, bandwidth utilization, and resource availability. Their effectiveness, however, depends on the quality of the input features, the selection of suitable algorithms, and the characteristics of the training data when learning is involved.

Deep learning extends traditional machine learning by using multilayer neural networks to learn complex representations from large datasets. Deep neural networks can be applied to traffic prediction, network anomaly detection, mobility analysis, intelligent resource allocation, and automated network management. Their ability to model nonlinear relationships can be beneficial when network behavior depends on several interacting variables. However, deep learning approaches may require substantial training data, computational resources, parameter tuning, and validation. Their internal decision-making processes can also be difficult to interpret, particularly when complex models are used for operational decisions.

In 6G network management, the choice between traditional machine learning and deep learning depends on the specific problem being addressed. Traditional machine learning may be suitable for structured network measurements and relatively well-defined classification or prediction tasks, whereas deep learning may be useful for more complex patterns involving large-scale or high-dimensional data. Nevertheless, neither approach is

universally superior. Their performance depends on the application, available data, computational constraints, evaluation methodology, and operational requirements. Furthermore, learning-based methods require appropriate training and testing data to establish their effectiveness.

The framework presented in this paper follows a simulation-driven and rule-based approach rather than implementing a traditional machine-learning or deep-learning model. It calculates network performance indicators such as availability, flow success rate, utilization, throughput, latency, bandwidth, active flows, and energy consumption. These indicators are evaluated by a rule-based optimization module that generates recommendations according to predefined conditions. For example, high network utilization can trigger recommendations for capacity expansion or traffic rerouting, while elevated latency can indicate the need to consider alternative lower-latency paths. Similarly, low availability can prompt recommendations for resource recovery. This design provides a transparent and computationally practical method for demonstrating intelligent network operations without requiring a separate model-training process. The recommendations are associated with explicit conditions, making their reasoning easier to inspect. However, the rule-based approach does not learn from historical data, discover previously unknown patterns automatically, or provide predictive capabilities equivalent to trained machine-learning models. Its effectiveness also depends on the thresholds and rules defined within the implementation.

Therefore, traditional machine learning, deep learning, and rule-based optimization should be considered complementary approaches rather than interchangeable solutions. Traditional machine learning and deep learning can potentially extend the framework through data-driven prediction and decision support, while the existing rule-based module provides interpretable operational recommendations based on simulated network measurements. Integrating and evaluating such learning-based extensions constitutes a possible direction for future research. In the current implementation, the primary focus remains on network simulation, digital twin state representation, capacity-aware routing, failure recovery, performance analytics, and explainable rule-based optimization.

V. PROBLEM STATEMENT

The increasing complexity of sixth-generation (6G) networks introduces significant challenges in network monitoring, traffic management, resource allocation, and operational reliability. The integration of heterogeneous network components, diverse traffic requirements, mobility, and dynamic communication links makes it difficult to evaluate network behavior using isolated management mechanisms. Changes in network conditions, such as link failures, insufficient capacity, and increased latency, can affect multiple traffic flows and reduce overall network performance. Therefore, an integrated simulation environment is required to represent these interactions and examine their effects under controlled conditions.

Existing network simulation and management approaches may focus on specific functions, such as routing, mobility, traffic analysis, or resource optimization, without providing a unified environment for examining their combined effects. Furthermore,

evaluating network performance requires consistent representations of network states and measurable indicators that reflect connectivity, traffic delivery, resource utilization, latency, throughput, and availability. Without integrating these aspects, it becomes difficult to analyze how network events influence overall operational performance and to identify suitable corrective actions.

Another important challenge is the interpretation of network performance measurements for operational decision-making. Although performance metrics can indicate congestion, excessive latency, resource failures, or inefficient energy utilization, these measurements must be connected to understandable recommendations to support effective network management. Complex learning-based optimization approaches may also introduce additional requirements for training data, computational resources, and model validation. Consequently, a practical framework should support network analysis while maintaining transparency in the reasoning behind its operational recommendations.

To address these challenges, this paper proposes a digital twin-based simulation and intelligent network operations framework for 6G networks. The framework integrates heterogeneous topology modeling, capacity-aware routing, traffic-flow management, network slicing, mobility modeling, propagation calculations, failure and recovery operations, digital twin snapshots, and performance analytics. A rule-based optimization module evaluates selected network indicators and generates interpretable recommendations for improving network conditions. The central objective is to provide a self-contained and reproducible simulation platform for analyzing 6G network behavior, evaluating the effects of operational events, and supporting transparent, metric-driven network management.

VI. RESEARCH GAP

Existing research on sixth-generation (6G) networks has extensively explored heterogeneous network architectures, digital twin technology, routing mechanisms, network slicing, mobility management, network resilience, and intelligent resource optimization. These research areas provide important foundations for developing adaptive and efficient network management systems. However, integrating these functions into a unified simulation environment remains an important practical challenge, particularly when the objective is to examine how changes in network topology, traffic demand, resource availability, and failure conditions influence overall network performance.

A major gap concerns the coordinated representation of network components and operational states. Network simulation approaches may emphasize individual aspects of communication systems, while digital twin architectures may focus on broader concepts of virtual representation, synchronization, and intelligent management. An integrated environment that combines heterogeneous node and link modeling with traffic-flow management, capacity-aware routing, mobility, propagation calculations, and failure recovery can provide a more comprehensive basis for studying interactions among these components. The need is not simply to represent network infrastructure, but also to examine how operational changes propagate through the simulated network.

Another gap relates to the joint evaluation of network performance and failure response. Routing decisions, link availability, traffic delivery, congestion, and resource utilization are closely connected, yet their combined effects require systematic evaluation under reproducible conditions. A simulation framework that supports failure injection, route recalculation, and performance measurement can help investigate these relationships. In particular, metrics such as availability, flow success rate, throughput, latency, and network utilization can provide a consistent basis for comparing network behavior across different simulated scenarios.

Furthermore, network analytics do not automatically provide actionable operational guidance. Performance indicators can reveal conditions such as excessive utilization, increased latency, low availability, or inefficient energy consumption, but operators also need understandable recommendations linked to these observations. Although learning-based optimization can support advanced decision-making, it may require training data, computational resources, and additional validation. A transparent rule-based approach provides an alternative for generating interpretable recommendations in a simulation environment, although its effectiveness depends on the defined rules and thresholds.

Based on these considerations, this paper addresses the following research gaps:

Integrated network modeling: The need for a unified simulation framework combining heterogeneous network topology, traffic flows, capacity-aware routing, slicing, mobility, propagation, and resource states.

Coordinated failure and routing analysis: The need to examine how node or link failures influence route availability, traffic delivery, and network performance within a controlled simulation environment.

Consistent digital twin state representation: The need to maintain structured, immutable snapshots of simulated network states to support inspection, serialization, and reproducible analysis.

Comprehensive performance evaluation: The need to evaluate multiple network indicators, including availability, flow success rate, utilization, throughput, latency, bandwidth, active flows, and energy consumption, within the same operational framework.

Interpretable optimization recommendations: The need to connect network performance measurements with transparent, rule-based recommendations that explain potential actions for addressing identified operational conditions.

Reproducible simulation-based investigation: The need for a self-contained environment that enables controlled experiments using deterministic synthetic telemetry without requiring live network infrastructure or external cloud services.

To address these gaps, the proposed framework integrates digital twin snapshot management, capacity-aware routing, network slicing, mobility modeling, propagation calculations, failure and recovery operations, performance analytics, and rule-based optimization within a graphical Network Operations Center environment. Its contribution lies in the integration of these implemented capabilities into a common simulation platform rather than in claiming a new deep-learning algorithm or a fully autonomous 6G network controller. The framework provides a foundation for reproducible investigation of network behavior, while comparative benchmarking, real-world validation,

advanced predictive models, and more detailed radio-network simulations remain important directions for future research.

VII. PROPOSED COMPARATIVE FRAMEWORK

The proposed comparative framework provides a structured approach for examining the capabilities of the developed digital twin-based simulation and intelligent network operations framework for 6G networks. Rather than evaluating a single network-management technique in isolation, the framework considers the relationship between network modeling, traffic management, routing, mobility, failure recovery, performance analytics, and operational optimization. These components are integrated to support the systematic observation of network behavior under different simulated conditions.

The framework begins with heterogeneous network representation, in which nodes and communication links are modeled using their respective properties and resource characteristics. Network nodes may represent base stations, edge computing resources, satellites, aerial platforms, IoT devices, and user equipment, while links contain attributes such as capacity, latency, reliability, and utilization. This representation provides the foundation for evaluating connectivity and resource availability across different network configurations.

The second component focuses on traffic management and routing. Traffic flows are assigned to feasible communication paths using a capacity-aware Dijkstra-based routing mechanism. The routing process considers link latency and available residual capacity, preventing the selection of links that cannot accommodate the required traffic demand. When network conditions change because of failures or resource availability, the framework supports route recalculation and rerouting to examine the resulting effects on traffic delivery and network performance.

The third component incorporates network slicing and mobility modeling. Traffic classes, including URLLC, eMBB, and mMTC, are represented to support differentiated traffic management and slice-related bandwidth accounting. Mobility modeling updates node positions and supports access-point selection based on proximity to active gNB or satellite nodes. These capabilities allow the framework to represent selected changes in network connectivity and investigate their implications for simulated network operations.

The fourth component addresses failure management and digital twin state representation. Failure and recovery operations enable controlled investigation of unavailable network resources and their effects on routing and connectivity. Immutable digital twin snapshots preserve structured representations of simulation states and support JSON serialization. This functionality provides a consistent basis for inspecting network conditions before and after operational events.

The fifth component performs network analytics and rule-based optimization. The framework calculates key performance indicators, including node availability, link availability, overall availability, flow success rate, network utilization, active flows, bandwidth, throughput, latency, and energy consumption. The optimization module evaluates selected indicators against predefined conditions and generates recommendations for congestion reduction, latency improvement, energy efficiency, and resource recovery. These recommendations are intended to

support operator decision-making rather than replace it with a learned or globally optimal control policy.

The comparative evaluation can be organized around the following dimension

Evaluation dimension	Purpose
Network representation	Examine the modeling of heterogeneous nodes, links, and resource properties.
Routing and traffic management	Evaluate feasible path selection, flow allocation, and rerouting behavior.
Network slicing	Examine differentiated traffic classes and slice-related bandwidth accounting.
Mobility and propagation	Assess the behavior of the implemented mobility and propagation models.
Failure and recovery	Investigate the effects of simulated failures on connectivity and traffic

VIII. SYSTEM FLOW AND OPERATION

The proposed digital twin-based 6G network simulation framework follows a sequence of interconnected operations, beginning with network initialization and proceeding through traffic generation, routing, performance monitoring, failure handling, and optimization recommendations. The workflow is designed to maintain a structured representation of network conditions while allowing the effects of operational changes to be examined through simulation. Each stage contributes to the overall process of modeling, analyzing, and monitoring the simulated network.

Network Initialization and Topology Creation: The process begins by initializing the simulation environment and creating the network topology. Nodes representing different network entities are configured with relevant properties, while communication links are established with attributes such as capacity, latency, reliability, and link status. The topology module maintains node and link relationships and supports the identification of available neighboring nodes. This initial configuration establishes the network structure on which subsequent operations depend.

Traffic Generation and Flow Management: After topology initialization, traffic flows are created to represent communication demands between network endpoints. Each flow has associated requirements that determine whether a feasible communication path can be established. Traffic management maintains flow information and supports the allocation and tracking of network resources. Traffic classes, including URLLC, eMBB, and mMTC, can be represented within the framework to support differentiated traffic handling and slice-related resource accounting.

Routing and Resource Allocation: The routing module determines feasible paths between source and destination nodes using a capacity-aware Dijkstra-based algorithm. Link latency is considered during path selection, while links with insufficient residual capacity

IX. COMPARATIVE EVALUATION ALGORITHM

The comparative evaluation algorithm provides a systematic procedure for examining network performance under different

simulated operating conditions using the proposed digital twin-based 6G network framework. The algorithm integrates topology initialization, traffic-flow creation, capacity-aware routing, network event processing, performance metric calculation, digital twin snapshot generation, and rule-based optimization. Its primary objective is to evaluate how changes in network conditions influence connectivity, traffic delivery, resource utilization, and overall network performance.

The evaluation begins by initializing the simulation environment and configuring the network nodes, communication links, and resource properties. Traffic flows are then created between selected source and destination nodes. For each flow, the routing mechanism identifies a feasible path based on link latency and residual capacity. If a suitable path is available, the flow can be allocated to that route; otherwise, the flow cannot be assigned a feasible route under the current conditions.

After establishing the initial network state, the algorithm calculates baseline performance metrics. These measurements provide a reference for evaluating subsequent scenarios. The network is then subjected to selected operational changes, such as increased traffic demand, node or link failures, mobility events, or resource recovery. Following each change, the framework updates the relevant network state and evaluates route availability and flow feasibility. Where possible, affected flows are rerouted through alternative paths.

The performance metrics are recalculated after each scenario to identify changes in network behavior. These metrics include node availability, link availability, overall availability, flow success rate, network utilization, active flows, bandwidth, throughput, latency, and energy consumption. The digital twin module generates a snapshot of the resulting network state, while the optimization module evaluates selected metrics and produces recommendations based on predefined rules. The results can then be compared with the baseline measurements to assess the effects of the simulated event.

Algorithm 1: Comparative Evaluation of the Proposed 6G Network Framework

Input: Network topology, node and link properties, traffic-flow demands, simulation configuration, and operational event scenarios.

Output: Performance metrics, digital twin snapshots, routing outcomes, and rule-based optimization recommendations.

Initialize the simulation environment and network components.

Create network nodes and communication links with their associated resource properties.

Configure traffic classes and create the required traffic flows.

Determine feasible routes using capacity-aware Dijkstra routing.

Allocate flows to feasible routes and record the initial network state.

Calculate baseline performance metrics.

Generate and store a digital twin snapshot of the baseline state.

Select an operational scenario, such as a traffic change, mobility event, node failure, link failure, or resource recovery.

Apply the selected event to the simulation.

Update the network state and identify affected flows.

Recalculate feasible routes and reroute affected flows where possible.

Recalculate network performance metrics.

Generate a digital twin snapshot of the updated state.

Evaluate selected metrics using the rule-based optimization module.

Record the generated recommendations and relevant operational logs.

Compare the updated metrics with the baseline measurements.

Repeat Steps 8–16 for the remaining scenarios.

Summarize the observed performance changes and routing outcomes.

Evaluation Metrics

The algorithm uses a common set of performance indicators to compare network conditions across the simulated scenarios.

Metric	Evaluation purpose
Node availability	Measures the proportion of 10odelled nodes that remain available.
Link availability	Measures the proportion of 10odelled links that remain available.
Overall availability	Represents the aggregate availability of the simulated network.
Flow success rate	Evaluates the proportion of flows successfully delivered according to the simulation's flow-success definition.
Network utilization	Examines the degree to which network resources are being used.
Active flows	Tracks the number of active traffic flows.
Bandwidth	Represents the bandwidth associated with the simulated network or active flows, according to the metric implementation.
Throughput	Measures the simulated rate of successful data delivery.
Latency	Represents the latency reported by the simulation model.
Energy consumption	Estimates network energy consumption using the implemented resource model.

For each scenario, the difference between a measured metric and its baseline value can be calculated as

$$\Delta M = M_{\text{scenario}} - M_{\text{baseline}}$$

where M_{scenario} represents the metric measured under the selected scenario and M_{baseline} represents its value under the initial configuration. For metrics where lower values are preferable, such as latency, a negative difference generally indicates an improvement. For metrics where higher values are preferable, such as flow success rate, a positive difference generally indicates an improvement. The interpretation depends on the metric definition and the scenario being evaluated.

The comparative evaluation algorithm provides a reproducible procedure for analyzing network behavior and examining the relationship between operational events and performance outcomes. Its results can be used to determine whether the implemented routing, failure-management, analytics, and recommendation mechanisms behave as expected under specified conditions. However, the algorithm itself does not establish that the proposed framework outperforms alternative approaches. Such conclusions require executed experiments, documented

configurations, repeated measurements where appropriate, and comparisons against clearly defined baseline methods.

X. MATHEMATICAL FORMULATION OF CANDIDATE MODELS

The mathematical formulation of the proposed framework describes the principal models used for network representation, capacity-aware routing, communication propagation, resource utilization, performance evaluation, and operational optimization. These formulations provide a quantitative basis for examining the behavior of the simulated 6G network under different traffic demands and operational events. The mathematical models presented in this section correspond to the implemented simulation capabilities; they do not assume the presence of an unimplemented deep-learning model or machine-learning-based optimizer.

A. Network Topology Model

The 6G network is represented as a graph:

$$G = (V, E)$$

where V denotes the set of network nodes and E denotes the set of communication links. Each node represents a network entity, such as a base station, edge computing node, satellite, IoT device, or user equipment. Each link represents a communication connection between two nodes.

A node $v_i \in V$ is associated with attributes such as resource capacity, status, position, utilization, and reliability. A link $e_{ij} \in E$, connecting nodes v_i and v_j , is characterized by its capacity, latency, reliability, utilization, and operational status.

The network can be expressed as

$$G = (V, E, \mathbf{X}_V, \mathbf{X}_E)$$

where $\mathbf{X}_V$ represents node attributes and $\mathbf{X}_E$ represents link attributes. This representation enables the framework to model heterogeneous infrastructure and evaluate how changes in node or link availability affect connectivity and traffic routing.

B. Capacity-Aware Routing Model

The routing mechanism identifies a feasible path between a source node s and a destination node d . Let a candidate path be represented by

$$P_{s,d} = (v_0, v_1, \dots, v_k)$$

where $v_0 = s$ and $v_k = d$. The total path latency is expressed as

$$L(P_{s,d}) = \sum_{e \in P_{s,d}} l_e$$

where l_e denotes the latency associated with link e .

For a traffic flow with demand b_f , a link is considered capacity-feasible when its residual capacity satisfies

$$C_e^{\text{res}} \geq b_f$$

where C_e^{res} is the residual capacity of link e . The capacity-aware routing problem can therefore be expressed as

$$P^* = \arg \min_{P \in \mathcal{P}_{s,d}} L(P)$$

subject to

$$C_e^{\text{res}} \geq b_f, \quad \forall e \in P$$

where $\mathcal{P}_{s,d}$ represents the candidate paths between the source and destination. Links that are unavailable or have insufficient residual capacity are excluded from the feasible path search.

The proposed framework uses a Dijkstra-based algorithm to determine the minimum-latency feasible path. If no feasible path exists, the flow cannot be assigned a valid route under the current network conditions. When failures or resource changes affect an existing route, the framework supports recalculating routes and rerouting affected flows where possible.

C. Propagation Delay Model

The propagation delay represents the time required for a signal to travel between two communication endpoints. For a propagation distance d , the delay can be estimated as

$$T_p = \frac{d n_r}{c}$$

where T_p is the propagation delay in seconds, d is the propagation distance in metres, n_r is the modeled refractive index, and c is the speed of light in vacuum.

To express propagation delay in milliseconds,

$$T_{p,ms} = \frac{d n_r}{c} \times 1000$$

This formulation supports the framework's propagation-delay calculations. It represents propagation time only and should not be interpreted as total end-to-end network latency, which may also include processing, queuing, transmission, and other modeled delays.

D. Free-Space Path Loss Model

The framework estimates free-space path loss (FSPL) to represent signal attenuation under idealized free-space propagation conditions. When distance is expressed in metres and frequency in hertz, the model is

$$FSPL_{dB} = 20\log_{10}(d) + 20\log_{10}(f) - 147.55$$

where d denotes the distance in metres and f denotes the carrier frequency in hertz.

The equation estimates the loss associated with free-space propagation. It does not incorporate environmental obstruction, multipath fading, atmospheric absorption, or interference. Therefore, the calculated value provides a simplified propagation estimate rather than a complete model of real-world wireless channel behavior.

E. Network Utilization Model

Network utilization indicates the extent to which communication resources are being used. For a link e , utilization can be represented as

$$U_e = \frac{C_e^{used}}{C_e} \times 100\%$$

where C_e^{used} is the used capacity and C_e is the total capacity of the link.

For a network containing a set of eligible links E' , an aggregate capacity-weighted utilization can be defined as

$$U_{net} = \frac{\sum_{e \in E'} C_e^{used}}{\sum_{e \in E'} C_e} \times 100\%$$

This aggregate expression is appropriate when the implementation's network utilization metric uses the corresponding capacity-weighted calculation. Otherwise, the paper should retain the exact aggregation method used by the implemented analytics module. Utilization measurements can

help identify heavily loaded links and support the interpretation of congestion-related recommendations.

F. Throughput and Bandwidth

Throughput represents the rate at which data is successfully delivered through the network. It can be expressed as

$$T = \frac{D_{delivered}}{\Delta t}$$

where $D_{delivered}$ denotes the amount of successfully delivered data during an observation interval Δt .

If the delivered data is measured in megabits and the observation interval in seconds, throughput is expressed in Mbps.

Bandwidth represents the available or allocated data-carrying capacity of a link or network resource. For an individual link, the used capacity must not exceed its total capacity:

$$0 \leq C_e^{used} \leq C_e$$

The distinction between bandwidth and throughput is important: bandwidth represents capacity, whereas throughput represents the achieved rate of successful data delivery. Their relationship depends on traffic demand, link conditions, routing, congestion, and the simulation's traffic-delivery model.

G. Latency Model

End-to-end latency can conceptually be decomposed into propagation, transmission, processing, and queuing components:

$$L_{e2e} = L_{prop} + L_{trans} + L_{proc} + L_{queue}$$

where L_{prop} represents propagation delay, L_{trans} represents transmission delay, L_{proc} represents processing delay, and L_{queue} represents queuing delay.

This decomposition provides a general analytical representation of communication latency. The implemented framework explicitly models link latency and propagation delay, but the complete equation should not be interpreted as a claim that every component is independently calculated by the current implementation. Experimental reporting should use the latency metric actually returned by the simulation analytics.

H. Availability Model

Network availability describes the proportion of network resources that are operational. For a set of nodes V , node availability can be represented as

$$A_V = \frac{N_{active}}{N_{total}}$$

where N_{active} is the number of active nodes and N_{total} is the total number of modeled nodes.

Similarly, link availability is

$$A_E = \frac{E_{active}}{E_{total}}$$

where E_{active} represents the number of active links and E_{total} is the total number of modeled links.

These equations express availability as a proportion between zero and one. The framework calculates node availability, link availability, and overall availability. The precise aggregation used for overall availability should follow the implemented analytics definition rather than assuming that it is necessarily the arithmetic mean of node and link availability.

I. Flow Success Rate

Flow success rate provides an indicator of successful traffic delivery. For an observation period containing F evaluated flows, it can be expressed as

$$S_f = \frac{F_{\text{success}}}{F_{\text{evaluated}}} \times 100\%$$

where F_{success} denotes the number of flows counted as successful and $F_{\text{evaluated}}$ denotes the total number of flows included in the evaluation.

The interpretation of this metric depends on the simulation's flow-success definition, including how successful delivery, failed routes, and incomplete flows are counted. It can be used to compare traffic delivery across baseline, failure, and recovery scenarios.

J. Energy Consumption Model

Energy consumption is an important consideration in heterogeneous 6G networks, particularly when evaluating resource efficiency across different node types. If the energy metric is represented as power consumption, the network-level value can be expressed as

$$P_{\text{net}} = \sum_{i=1}^N P_i$$

where P_i is the power attributed to node i and N is the number of nodes included in the calculation.

Energy consumed over an observation interval can be calculated as

$$E_{\text{net}} = \int_{t_0}^{t_1} P_{\text{net}}(t) dt$$

where E_{net} represents energy consumed between times t_0 and t_1 . The distinction between power and energy must be maintained: power is measured in watts, whereas energy is measured in joules or watt-hours. Since the implemented analytics reports network energy in watts, the reported metric should be treated as power consumption unless the simulation explicitly integrates power over time.

K. Rule-Based Optimization Model

The optimization module evaluates selected network metrics and generates recommendations according to predefined conditions. Let the network metric vector be represented by

$$\mathbf{m} = [U_{\text{net}}, L_{\text{net}}, R_{E/T}, A_{\text{net}}]$$

where U_{net} represents network utilization, L_{net} represents latency, $R_{E/T}$ represents the implemented energy-to-throughput indicator, and A_{net} represents network availability.

The recommendation function can be represented as

$$\mathcal{R} = g(\mathbf{m})$$

where g denotes the predefined rule-based decision function and $\mathcal{R}$ represents the resulting recommendation.

The implemented optimization rules include the following conditions:

If network utilization exceeds 85%, recommend capacity expansion or rerouting high-demand flows.

If latency exceeds 10 ms, recommend rebalancing traffic toward lower-latency links.

If the energy-to-throughput indicator exceeds 20, recommend consolidating underused nodes.

If availability falls below 0.99, recommend recovering failed resources.

Otherwise, report that the topology is within the configured targets.

These conditions describe operational recommendations, not guaranteed improvements. Their practical effectiveness depends on the network configuration, metric definitions, and whether the recommended action can be carried out successfully.

L. Comparative Performance Formulation

To compare network behavior under different simulated conditions, let M_b represent a metric measured in the baseline scenario and M_s represent the same metric under a selected scenario. The absolute change is

$$\Delta M = M_s - M_b$$

For a nonzero baseline, the percentage change is

$$\Delta M_{\%} = \frac{M_s - M_b}{M_b} \times 100\%$$

The percentage-change equation is undefined when $M_b = 0$, in which case the absolute difference should be reported instead.

For metrics such as throughput, availability, and flow success rate, an increase may indicate improvement. For metrics such as latency and resource utilization under congested conditions, a decrease may be desirable. However, utilization should not always be minimized because low utilization can indicate unused capacity. The interpretation of every metric must therefore reflect its operational objective and the scenario under evaluation.

Overall, these mathematical formulations provide a quantitative foundation for representing the network, determining feasible routes, estimating propagation characteristics, measuring operational performance, and generating rule-based recommendations. They support the analysis of simulated 6G network behavior without assuming that the current framework implements deep-learning-based prediction or machine-learning-based optimization. The resulting metrics and snapshots can be used in subsequent experiments to compare baseline and modified network conditions systematically.

XI. SIMULATION ENVIRONMENT AND EXPERIMENTAL SETUP

A. Simulation Environment

The proposed digital twin-based 6G network framework is implemented as a self-contained simulation environment using Python. Unlike data-driven approaches that require external datasets for model training and testing, the proposed framework generates and processes network states through its simulation mechanisms. It uses deterministic synthetic telemetry to represent network conditions and support controlled experimentation without relying on external datasets, live network measurements, or cloud services.

The simulation environment models heterogeneous network components, including base stations, edge computing nodes, satellites, aerial platforms, IoT devices, and user equipment. Communication links are represented using attributes such as capacity, latency, reliability, utilization, and operational status. These properties provide the foundation for network topology management, traffic-flow allocation, capacity-aware routing, mobility modeling, failure recovery, and performance evaluation.

B. Network Configuration

The network configuration consists of interconnected nodes and communication links with defined resource properties. Traffic flows are created between selected source and destination nodes, and the routing mechanism identifies feasible paths according to link latency and residual capacity. The framework also incorporates URLLC, eMBB, and mMTC traffic classes, mobility-state modeling, propagation calculations, and failure and recovery operations.

The initial network configuration serves as the baseline for evaluating subsequent operational scenarios. Changes to traffic demand, resource availability, node status, or link status can be introduced to examine their effects on network connectivity and performance.

C. Experimental Scenarios

The experimental evaluation can be organized around a baseline configuration and controlled network events. These scenarios include normal network operation, changes in traffic demand, link or node failures, resource recovery, mobility events, and network slicing operations. Each scenario provides an opportunity to examine how the implemented routing, traffic-management, and recovery mechanisms respond to changing network conditions.

The baseline scenario establishes the initial performance measurements. Subsequent scenarios are evaluated by comparing their results with these baseline measurements. Failure scenarios can be used to examine route availability and flow success, while traffic and resource changes can be used to investigate network utilization, throughput, and latency. The optimization module can also be examined to determine whether its recommendations correspond to the predefined rules and observed network metrics.

D. Performance Evaluation Metrics

The framework evaluates network behavior using the performance indicators provided by its analytics module. These include node availability, link availability, overall availability, flow success rate, network utilization, active flows, bandwidth, throughput, latency, and energy-related measurements. These metrics provide a consistent basis for examining the effects of different simulated operating conditions.

Digital twin snapshots and operation logs support the inspection of network states and the recording of changes associated with selected events. The measurements obtained from each scenario can be compared with the baseline to identify variations in resource availability, traffic delivery, and network performance.

E. Experimental Procedure

The evaluation begins by initializing the network topology and configuring node and link properties. Traffic flows are then created, feasible routes are identified, and baseline performance metrics are calculated. A digital twin snapshot is generated to represent the initial network state.

Next, a selected operational event is introduced into the simulation. The network state is updated, affected routes are reassessed, and rerouting is performed where feasible. The analytics module then calculates the resulting performance metrics, and a new digital twin snapshot records the updated

state. This procedure can be repeated for different scenarios to examine changes in network behavior.

The difference between a metric measured under a scenario and its baseline value can be expressed as

$$\Delta M = M_{\text{scenario}} - M_{\text{baseline}}$$

where M_{scenario} represents the measured value under the selected condition and M_{baseline} represents the corresponding initial value.

Overall, the experimental setup enables controlled and reproducible investigation of the proposed 6G network framework without requiring an external dataset. The evaluation focuses on simulation-based network behavior, performance metrics, failure response, routing outcomes, and rule-based operational recommendations. The resulting observations must be interpreted within the scope of the implemented simulation models rather than as measurements from a physical 6G deployment.

XII. COMPARATIVE RESULTS AND DISCUSSION

Table II presents representative accuracy results reported in previous studies for the six candidate architectures using different datasets and embedding methods. The noticeable variation in results within each architecture shows that accuracy from a single study is not enough to determine which architecture is the best. Performance can change considerably depending on factors such as dataset size, class distribution, preprocessing, and the type of embeddings used.

TABLE II. REPRESENTATIVE REPORTED ACCURACY BY ARCHITECTURE (SELECTED STUDIES)

Architecture	Reported Range	Accuracy	Representative Source(s)
CNN (document-level)	~55–65%		[18]
LSTM / GRU	~40–75%		[2], [9]
BiLSTM			
Hybrid CNN-RNN	~60–78%		[3], [4]
LSTM + Transformer embeddings	up to ~87%		[7]
BERT + CNN	highest among tested combos		[1], [6]
Fine-tuned Transformer (BERT/RoBERTa)	~75–86%		[8], [11], [12]

Three main patterns can be observed from the results reported across the reviewed studies. First, models that use pre-trained contextual embeddings, either as fixed features or through fine-tuning, generally perform better than models trained from scratch with randomly initialised static embeddings on the same dataset. This is similar to the improvement observed when additional linguistic features such as TF-IDF and LIWC are used in traditional machinelearning approaches [7], [8], [20]. Second, hybrid models that combine contextual embeddings with a lightweight CNN or recurrent layer, such as BERT-CNN and BERTLSTM, often achieve results comparable to or better than a fully fine-tuned Transformer classifier. At the same time, they can reduce the number of parameters that need to be updated during training [1], [6], [8]. Third, there is no consistently superior recurrent architecture among LSTM, BiLSTM, and GRU. Their performance depends on factors such as the dataset,

embedding method, and personality dimension being predicted [2], [15].

TABLE III. QUALITATIVE COMPARISON ACROSS PERSONALITY DIMENSIONS

Dimension	Architectures Typically Favoured	Notes
Introversion/Extraversion (I/E)	CNN, BiLSTM	Strong lexical cues; simpler models competitive
Sensing/Intuition (S/N)	BiLSTM, BERT-based	Benefits from longer context
Thinking/Feeling (T/F)	Fine-tuned Transformer	Weaker lexical cues; contextual embedding helps most
Judging/Perceiving (J/P)	Fine-tuned Transformer, hybrid	Hardest dimension across most studies

It is important to remember that accuracy values reported across different studies are not always directly comparable. Differences in test settings, embedding dimensions, and maximum sequence lengths can affect the reported results even when the underlying architecture remains the same. Similarly, studies that handle class imbalance using weighted loss functions or resampling may report lower overall accuracy but higher macro-F1 scores compared with studies that use the original imbalanced data [9], [20]. Therefore, the exact percentage differences in Tables II and III should be interpreted carefully. The more useful observation is the overall performance trend: contextualembedding models generally achieve the strongest results, while basic CNN and RNN models are usually faster but show greater variation. Hybrid models provide a practical balance between performance and computational requirements.

XII. COMPARATIVE RESULTS AND DISCUSSION

A. Overview of Comparative Evaluation

The proposed digital twin-based 6G network framework integrates network topology management, capacity-aware routing, traffic-flow management, network slicing, mobility modeling, failure recovery, performance analytics, and rule-based optimization. Its evaluation focuses on examining the behavior of these components under different simulated network conditions. Since the framework operates using synthetic telemetry rather than an external dataset, the comparative analysis is based on simulated network states and the performance metrics generated during execution.

The evaluation considers a baseline network configuration and alternative operating scenarios involving traffic changes, resource constraints, network failures, recovery operations, and mobility events. The purpose is to determine how these conditions affect network connectivity, traffic delivery, resource utilization, and operational recommendations. Numerical comparisons must be obtained from actual simulation runs before quantitative performance claims can be made.

B. Network Availability and Failure Analysis

Network availability is an important indicator of the operational condition of a communication network. In the proposed

framework, node and link availability are monitored to identify changes in the number of available network resources. Under the baseline configuration, the initial resource states provide a reference for examining subsequent failures and recovery events. When a node or link becomes unavailable, the routing mechanism can be used to reassess path feasibility. If an alternative path satisfies the routing constraints, affected flows may be rerouted. If no feasible path exists, communication between the corresponding endpoints may remain unavailable. These outcomes can be evaluated using node availability, link availability, overall availability, and flow success rate.

The comparison between baseline and failure scenarios can therefore help establish the extent to which resource disruptions affect simulated network operation. Recovery scenarios can subsequently be used to examine whether the restoration of resources improves connectivity and enables previously infeasible routes. The magnitude of these effects must be determined from the recorded simulation results.

C. Routing and Traffic-Flow Performance

The proposed framework uses capacity-aware Dijkstra routing to identify feasible communication paths. Unlike a shortest-path method that considers only path cost, the implemented routing mechanism also excludes links whose residual capacity is insufficient for the requested traffic demand. This supports route selection under explicit resource constraints.

The routing evaluation should examine whether feasible paths are identified for different source-destination pairs and whether affected flows can be rerouted following changes in link availability. Relevant measurements include flow success rate, throughput, latency, and the number of active flows.

Under resource-constrained conditions, the existence of a low-latency path does not necessarily guarantee that a flow can be allocated to it, because the available capacity must also satisfy the flow's demand. Similarly, the availability of an alternative route does not automatically establish improved throughput or reduced latency. Such improvements depend on the characteristics of the alternative path and must be confirmed through experimental measurements.

D. Network Utilization and Traffic Management

Network utilization provides an indication of how heavily communication resources are being used. In the proposed framework, utilization metrics can be examined under different traffic demands and resource configurations. Increasing traffic demand or reducing available capacity may change the utilization of individual links and influence route feasibility.

The analytics module provides network utilization, active-flow, bandwidth, and throughput indicators for examining these conditions. Comparing the corresponding measurements across scenarios can help identify changes in resource usage and traffic delivery.

The optimization module uses a predefined utilization threshold of 85% to generate recommendations

XIII. COMPUTATIONAL COST AND TRAINING INFRASTRUCTURE ANALYSIS

The computational cost of a 6G network operations framework depends on the complexity of network topology, routing decisions, traffic generation, mobility events, failure handling, digital-twin state management, and real-time analytics. Unlike deep learning-based approaches that require model training and large-scale datasets, the proposed framework primarily relies on simulation-driven network models and rule-based optimization mechanisms. Therefore, its computational requirements are associated mainly with simulation execution, resource-aware routing, telemetry processing, network-state updates, and visualization rather than neural network training.

The proposed framework is implemented using Python and PySide6, with a modular architecture that separates the network models, simulation logic, digital-twin operations, analytics, and graphical interface. This separation supports independent execution and testing of the core simulation components. The simulation uses locally generated synthetic telemetry and does not require an external dataset, cloud infrastructure, or dedicated model-training environment. Consequently, the framework can be operated in a local computing environment, subject to the processing and memory requirements of the selected network topology and simulation workload.

Routing represents one of the principal computational operations in the framework. The capacity-aware Dijkstra algorithm identifies feasible paths by considering link latency and available residual capacity. Its computational cost depends on the number of network nodes and links, as well as the data structure used to represent the topology. For a conventional implementation using a priority queue, the approximate time complexity of a single Dijkstra search is $O((V + E)\log V)$, where V denotes the number of nodes and E denotes the number of links. When routing is repeatedly evaluated for multiple traffic flows or after topology changes, the overall computational workload increases with the number of routing requests and the frequency of network events. Digital-twin operations introduce additional processing requirements through state synchronization, immutable snapshot creation, and JSON serialization. The framework maintains representations of network resources and their operational states, enabling the system to evaluate topology changes, failures, recovery operations, and traffic conditions. The cost of generating and storing snapshots depends on the number of modeled resources and the amount of state information retained in each snapshot. Similarly, analytics operations calculate indicators such as network utilization, throughput, latency, availability, flow success rate, active flows, and energy consumption. Their execution cost depends on the volume of simulation data and the frequency at which metrics are updated.

The graphical monitoring interface also contributes to the overall computational workload. KPI cards, topology visualization, alarms, traffic indicators, and network analytics graphs require periodic updates as the simulation progresses. Increasing the number of monitored resources, plotted metrics, and historical observations may increase memory consumption and rendering overhead. Therefore, the simulation engine and visualization layer should be evaluated separately when investigating responsiveness and scalability, particularly when the framework is extended to support larger network topologies or higher-frequency telemetry updates.

In terms of training infrastructure, the current framework does not require a neural network training pipeline because its implemented routing and optimization mechanisms are based on algorithmic and rule-based operations. It does not depend on GPU-based model training, distributed training infrastructure, or an external machine-learning dataset for its core simulation functionality. The optional use of machine learning for predictive analytics or intelligent decision-making could be investigated in future extensions; however, such functionality would require a separately defined model, suitable training data, an evaluation procedure, and additional computational measurements. These extensions should not be interpreted as components of the current implementation.

A comprehensive computational evaluation should record execution time for routing, simulation updates, snapshot generation, analytics calculations, and failure-recovery operations. Memory consumption, CPU utilization, interface responsiveness, and execution time under increasing network sizes should also be measured. Experiments should compare multiple topology sizes and traffic workloads under consistent hardware and software configurations. Since measured runtime, memory usage, and hardware specifications have not been established in the available project information, numerical claims about computational efficiency or maximum supported network size cannot be reported reliably at this stage.

Overall, the framework adopts a simulation-oriented design that avoids the training overhead associated with deep learning-based network-management systems. Its practical scalability, however, must be established through controlled performance measurements. Such an evaluation would provide a clearer understanding of the relationship between topology size, event frequency, routing workload, digital-twin operations, and monitoring overhead, thereby identifying potential bottlenecks and opportunities for future optimization.

XIV. EXPLAINABILITY AND INTERPRETABILITY TECHNIQUES

Explainability and interpretability are important aspects of intelligent network management because network operators need to understand the reasons behind routing decisions, performance variations, resource failures, and optimization recommendations. In a 6G network environment, where different communication technologies, traffic categories, and resource constraints interact, transparent decision-making can help operators identify network issues and evaluate the suitability of recommended actions. The proposed framework addresses interpretability primarily through observable simulation states, network performance metrics, operational logs, and rule-based optimization recommendations. The framework maintains structured representations of network nodes, communication links, and their operational properties. Node information includes resource capacity, load, reliability, energy-related attributes, and operational status, while link information includes capacity, latency, reliability, packet loss, jitter, signal quality, congestion, and utilization. These attributes provide contextual information for examining network behavior. When a link becomes unavailable, a node fails, or traffic conditions change, the resulting changes in topology and

performance metrics can be inspected to understand their effects on network operations.

Routing decisions provide another source of interpretability. The capacity-aware Dijkstra algorithm selects feasible paths according to link latency while excluding links that do not have sufficient residual capacity for the requested traffic demand. Consequently, routing behavior can be examined in relation to path availability, latency, and capacity constraints. If no feasible route exists, the network state and link conditions can be investigated to identify possible causes. This approach provides an algorithmic basis for understanding routing outcomes rather than relying on an opaque prediction model.

The framework also incorporates rule-based optimization checks that connect observed network conditions with operational recommendations. For example, network utilization above 85% triggers a recommendation to increase capacity or reroute high-demand flows. Latency above 10 ms prompts a recommendation to rebalance traffic toward lower-latency links. An energy-to-throughput ratio above 20 leads to a recommendation to consolidate underused nodes, while network availability below 0.99 triggers a recommendation to recover failed resources. These rules make the optimization logic more transparent because each recommendation is associated with an identifiable metric and a predefined threshold. The recommendations should be understood as decision-support outputs; they do not, by themselves, demonstrate that a suggested action has been executed or that the resulting network performance has improved.

Digital-twin snapshots and operational logs further support traceability. The framework can create immutable snapshots of network state and serialize them into JSON, allowing the represented state to be inspected and retained for analysis. Failure, recovery, and optimization records can help operators examine the sequence of simulated events and the associated changes in network behavior. Together, these mechanisms support reproducibility and make it easier to compare network conditions before and after a simulated event.

The monitoring interface contributes to interpretability by presenting key performance indicators, network topology, traffic information, alarms, and analytics graphs. These visual elements allow operators to observe changes in latency, throughput, utilization, availability, and other indicators during simulation. By presenting network conditions alongside operational events and optimization recommendations, the interface supports a more understandable view of the simulation process. However, visualization alone does not establish the causal relationship between an event and a performance change; such relationships must be evaluated using the underlying simulation records and controlled experiments.

Unlike explainable deep learning approaches such as SHAP or Grad-CAM, which are designed to interpret predictions from particular machine-learning models, the current framework does not depend on a trained neural network for its core routing and optimization functions. Therefore, these model-specific explanation techniques are not required for the implemented system. Its interpretability is instead based on explicit routing constraints, measurable network attributes, predefined optimization rules, inspectable simulation states, and operational records. SHAP, Grad-CAM, or other model-explanation methods

would become relevant only if suitable machine-learning prediction components were introduced in a future extension.

Overall, the framework supports operational transparency by making network conditions, routing constraints, performance metrics, and optimization rules accessible for inspection. This design helps operators understand how the simulated network behaves under changing traffic conditions, resource failures, and recovery scenarios. Future evaluation can strengthen this capability by measuring how accurately recommendations correspond to observed network conditions, how consistently results can be reproduced, and how effectively operators can use the available information to diagnose simulated network problems.

XV. THREATS TO VALIDITY

The validity of the proposed digital twin-based simulation and intelligent network operations framework depends on the accuracy of its simulation models, the representativeness of the modeled network conditions, and the consistency of the evaluation procedure. Although the framework provides a controlled environment for examining network behavior under different operational scenarios, several limitations must be considered when interpreting its results.

Construct Validity: Construct validity concerns whether the selected metrics adequately represent the network characteristics being investigated. The framework uses indicators such as latency, throughput, network utilization, availability, flow success rate, and energy consumption to assess network behavior. However, these metrics represent only selected aspects of network performance. Their interpretation depends on how they are calculated, how frequently they are updated, and whether their definitions accurately reflect the intended operational objectives. In particular, simulated energy-related values should not automatically be interpreted as measurements of physical network power consumption.

Internal Validity: Internal validity relates to whether observed performance changes can be attributed to the simulated event or operational action under investigation. Network behavior may be influenced by several interacting factors, including routing decisions, traffic demand, resource availability, mobility events, and link failures. If multiple conditions change simultaneously, it may be difficult to determine which factor caused a particular outcome. Controlled experiments that modify one parameter at a time, maintain consistent initial conditions, and record relevant state changes can help reduce this uncertainty.

Model Validity: The framework uses software-defined representations of network nodes, links, traffic classes, propagation characteristics, and operational states. These models provide a basis for simulation, but they cannot fully reproduce every characteristic of a real 6G deployment. Actual networks may experience environmental interference, complex radio-channel behavior, hardware limitations, protocol interactions, and unpredictable user mobility. Consequently, results obtained from the simulator should be interpreted as evidence about the

modeled scenarios rather than direct proof of equivalent performance in operational 6G infrastructure.

External Validity: External validity concerns the extent to which the findings can be generalized beyond the tested simulation environment. The framework generates synthetic telemetry locally and does not use an external dataset or measurements collected from a deployed 6G network. Although synthetic inputs allow controlled and repeatable experiments, they may not capture the full diversity of real-world traffic patterns, propagation conditions, mobility behavior, or network failures. Therefore, conclusions should be limited to the scenarios and configurations evaluated until the framework is validated against suitable real-world measurements or independent simulation environments.

Parameter and Configuration Validity: Simulation outcomes may depend on the selected topology, link capacities, latency values, traffic demands, resource attributes, propagation parameters, and optimization thresholds. For example, the recommendations produced by the rule-based optimization component depend on predefined conditions for utilization, latency, energy-to-throughput ratio, and availability. Different parameter settings may produce different recommendations and performance outcomes. Documenting these settings and conducting sensitivity analyses are necessary to determine whether the conclusions remain consistent under alternative configurations.

Reproducibility and Statistical Validity: The use of deterministic synthetic simulation behavior supports repeatable execution under the same configuration. However, deterministic results alone do not establish that the framework performs reliably across a broad range of possible network conditions. Evaluation across multiple topologies, traffic workloads, failure scenarios, and parameter settings would provide stronger evidence of consistency. Where randomized scenarios are introduced, repeated runs with different random seeds and appropriate statistical summaries should be used. Since numerical experimental results and repeated-run statistics have not yet been established, no statistical significance or quantitative superiority over alternative approaches can currently be claimed.

Performance and Scalability Validity: The computational behavior of the framework may change as the number of network nodes, links, traffic flows, simulation events, and monitored metrics increases. Routing, snapshot creation, analytics processing, and graphical updates may contribute differently to execution time and memory consumption as the workload grows. Without systematic measurements across different network sizes and controlled hardware configurations, the maximum practical scale and computational efficiency of the framework remain undetermined.

In summary, the proposed framework provides a controlled and inspectable environment for studying simulated 6G network operations, but its findings must be interpreted in relation to the assumptions, parameters, and scenarios represented in the implementation. The absence of external datasets, real-world network measurements, and completed quantitative

benchmarking limits the extent to which its results can be generalized. Future work should address these limitations through controlled comparative experiments, sensitivity analysis, repeated simulation runs where appropriate, computational profiling, and validation against independent network models or real-world measurements when they become available.

XVI. ARCHITECTURE SELECTION: IDENTIFYING THE SIMPLEST AND MOST SUITABLE DEEP LEARNING MODEL

Selecting an appropriate deep learning architecture for 6G network operations requires consideration of computational complexity, prediction accuracy, training requirements, inference latency, and suitability for network telemetry. Although complex neural architectures may provide advantages for learning sophisticated network patterns, their benefits must be evaluated against the additional computational resources and training requirements they introduce. For the proposed digital twin-based framework, a lightweight model is preferable as an initial extension because the existing system already provides structured network metrics and simulation-generated telemetry.

A multilayer perceptron (MLP) is a suitable starting point for learning from structured network data. The model can accept features such as network utilization, latency, throughput, packet loss, link congestion, resource availability, and traffic demand. These features can be used to predict a selected operational target, such as network congestion, a potential performance degradation, or a resource utilization category. An MLP has a relatively straightforward architecture consisting of an input layer, one or more fully connected hidden layers, and an output layer. Compared with architectures designed for image processing or complex sequential data, it is comparatively simple to implement, train, and deploy for tabular telemetry.

A lightweight multilayer perceptron can be trained using synthetic telemetry generated by the simulation framework. The data would first need to be collected and labeled according to the prediction task. The resulting dataset could then be divided into training, validation, and testing subsets. Feature normalization, suitable loss functions, and early stopping could be applied to support stable training and reduce unnecessary computational overhead. However, because the current project does not include a trained deep learning model or an established labeled training dataset, this workflow represents a proposed extension rather than an existing capability.

A temporal model such as a gated recurrent unit (GRU) could be considered when the objective is to predict future network conditions from sequences of telemetry observations. Unlike an MLP that processes a fixed feature vector, a GRU can learn temporal dependencies across successive observations. This may be useful for forecasting traffic demand, detecting developing congestion patterns, or predicting changes in network performance. Nevertheless, a GRU requires sequential training examples and introduces additional architectural and training complexity. It is therefore more appropriate when temporal prediction is an explicit research objective rather than a requirement for basic network-state analysis.

A Transformer-based model could also be investigated for learning relationships across longer telemetry sequences or

multiple interacting network indicators. However, its suitability would depend on the size and characteristics of the available training data, the prediction task, and the computational resources. For an initial implementation based on structured synthetic telemetry, a Transformer may introduce unnecessary complexity compared with a smaller MLP or GRU.

Considering implementation simplicity and the current simulation-oriented architecture, the multilayer perceptron is the most practical initial deep learning candidate for structured telemetry prediction. It offers a clear training workflow and can be integrated with the existing digital twin through a separate prediction component. The model could generate forecasts or risk estimates, while the current routing algorithms and rule-based optimization mechanisms continue to manage routing feasibility and operational recommendations. This separation would allow predictive intelligence to be introduced without replacing the established simulation and network-management components.

However, the simplest architecture cannot automatically be considered the most accurate or the best-performing model. The final selection should be based on experiments comparing an MLP with appropriate alternatives, including a GRU when temporal information is relevant. Evaluation should consider prediction quality, inference latency, training time, memory consumption, and robustness across different network topologies and traffic conditions. Traditional machine learning models may also provide useful baselines for structured telemetry, even though they are not deep learning architectures.

In conclusion, a lightweight MLP is recommended as the initial architecture to investigate for adding deep learning-based prediction to the proposed 6G network operations framework. A GRU is a reasonable alternative when forecasting temporal network behavior is the primary objective. Since neither model has been established as implemented or experimentally validated in the current project, the recommendation is based on architectural suitability and simplicity rather than measured superiority. Comparative experimentation is required to determine which model provides the best balance between predictive performance and computational cost.

XVII. ABLATION STUDY: CONTRIBUTION OF EMBEDDING CHOICE

An ablation study is an experimental approach used to determine how individual components of a model or system influence its overall performance. In the proposed digital twin-based 6G network operations framework, the representation of network telemetry is an important consideration if a deep learning prediction component is introduced. Network indicators such as latency, throughput, bandwidth utilization, packet loss, congestion, and resource availability can be represented in different ways before being supplied to a learning model. Comparing these representations can help determine whether the selected feature encoding contributes meaningfully to prediction accuracy and computational efficiency.

Unlike natural language processing applications, where word or sentence embeddings are commonly used to represent semantic information, the current framework primarily operates on structured numerical network attributes and categorical network properties. Therefore, conventional text embeddings are not

directly required for its existing routing and optimization operations. For a future deep learning extension, the term *embedding choice* can refer more broadly to the representation of numerical and categorical telemetry features before they are processed by the prediction model.

The proposed ablation study would compare multiple telemetry representation strategies while keeping the prediction task, model architecture, data partitions, training procedure, and evaluation conditions consistent. The first configuration would use normalized numerical features alongside appropriately encoded categorical variables. The second configuration could introduce learned embeddings for categorical attributes, such as node type, link type, traffic class, or operational status. A third configuration could evaluate a combined representation in which normalized numerical features are concatenated with learned categorical embeddings. These alternatives would help determine whether learned representations provide advantages over simpler feature encoding for the selected task.

In the baseline configuration, numerical telemetry features would be scaled using parameters estimated from the training data, while categorical variables would be represented using a suitable encoding method, such as one-hot encoding. This configuration would provide a relatively simple reference for evaluating the contribution of more complex representations. In the learned-embedding configuration, categorical values would be mapped to trainable low-dimensional vectors. These vectors could capture recurring associations among categories when sufficient representative training examples are available. The combined configuration would integrate the learned categorical representations with the numerical telemetry features before passing them to the prediction network.

The evaluation should use a clearly defined prediction objective, such as congestion classification, resource utilization prediction, or performance degradation forecasting. For classification tasks, appropriate metrics may include accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve. For numerical forecasting tasks, mean absolute error and root mean squared error may be more appropriate. Computational measurements, including training time, inference latency, and memory consumption, should also be recorded to determine whether any predictive improvement justifies the additional complexity introduced by learned embeddings.

To ensure a fair comparison, all configurations should use the same training, validation, and test partitions, and preprocessing parameters should be learned exclusively from the training data. The model architecture and training settings should remain consistent wherever possible, with changes limited to the feature representation being investigated. Repeated runs may be used when stochastic training or data generation affects the results. These controls would help isolate the contribution of embedding choice rather than attributing differences to unrelated changes in the experimental setup.

The ablation study should also consider whether the benefit of learned embeddings varies across network conditions. For example, categorical representations may be more useful when the dataset contains diverse node types, link technologies, and traffic classes. Conversely, a simple encoding strategy may be sufficient when the categorical variables have few distinct values

or when the available training data is limited. These possibilities should be evaluated empirically rather than assumed in advance.

The current project information does not establish an implemented embedding module, a trained deep learning prediction model, or experimental results comparing alternative embeddings. Consequently, no quantitative improvement can be attributed to a particular representation at this stage. The proposed ablation study provides an experimental plan for a future predictive extension and should be reported as completed only after the configurations have been implemented and evaluated.

In summary, this ablation study would investigate whether learned categorical embeddings improve the representation of structured 6G network telemetry compared with simpler encoding techniques. By controlling other experimental variables and measuring both predictive performance and computational cost, the study could identify a suitable representation strategy for integrating deep learning-based prediction into the existing digital twin framework. The final selection should prioritize measurable benefits, implementation simplicity, and compatibility with the framework's simulation-driven architecture.

XVIII. CONCLUSION AND FUTURE WORK

The proposed digital twin-based simulation and intelligent network operations framework provides a software-based environment for modeling, monitoring, and analyzing network behavior in the context of emerging 6G communication systems. The framework integrates network topology management, capacity-aware routing, traffic simulation, propagation modeling, mobility events, network slicing, failure handling, recovery operations, and performance analytics within a modular architecture. By combining these capabilities, the system supports the examination of network conditions and operational changes through controlled simulation scenarios.

A key aspect of the framework is its integration of network-state management with digital twin snapshots and operational monitoring. The simulation maintains structured representations of network nodes, communication links, traffic flows, and resource attributes, enabling network conditions to be examined as operational events occur. The capacity-aware Dijkstra routing mechanism identifies feasible paths according to link latency and available residual capacity, while the analytics components provide indicators such as throughput, latency, utilization, availability, and flow success rate. In addition, rule-based optimization checks connect selected performance thresholds with recommendations for capacity management, traffic rerouting, resource consolidation, and failure recovery.

The framework also emphasizes interpretability through explicit routing constraints, observable network metrics, operational records, and visual monitoring components. These features allow users to inspect simulated network states and investigate changes associated with traffic variations, failures, and recovery operations. The use of locally generated synthetic telemetry enables controlled experimentation without requiring an external dataset or a live network deployment. Furthermore, the separation of simulation logic from the graphical interface

supports modular development and provides a foundation for extending the system with additional analytical capabilities.

However, the current implementation should be understood as a simulation and network operations framework rather than a fully validated 6G deployment model. Its behavior depends on the assumptions, parameters, and scenarios represented in the simulator. Although the system includes algorithmic routing and rule-based optimization, a trained deep learning model is not established as part of the current core implementation. Similarly, quantitative claims regarding performance improvements, scalability, computational efficiency, or superiority over alternative approaches require systematic experimental measurements. Validation against independent simulation environments or real-world network observations would further strengthen the applicability of the framework.

Future work can extend the framework in several directions. First, more comprehensive experimental evaluation can be conducted using different network topologies, traffic workloads, mobility patterns, link failures, and recovery scenarios. Such experiments should measure routing performance, throughput, latency, availability, flow success rate, and resource utilization under consistent configurations. Repeated simulation runs and sensitivity analyses can help establish the consistency of the observed behavior across different operating conditions.

Second, a predictive intelligence component could be introduced to estimate future network conditions and identify potential performance degradation. A lightweight multilayer perceptron (MLP) could serve as an initial candidate for structured telemetry prediction, while a gated recurrent unit (GRU) could be investigated for temporal forecasting. These models would require suitable training examples, defined prediction targets, and independent evaluation. Their usefulness should be assessed by comparing predictive quality, inference latency, memory consumption, and training cost against appropriate baseline methods.

Third, the digital twin could be extended to support more detailed modeling of radio propagation, interference, handover behavior, heterogeneous network resources, and interactions among different network slices. Additional studies could investigate how resource allocation and routing decisions affect the performance of enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC). Such extensions would require clearly defined models and validation procedures to ensure that the simulated behavior remains meaningful.

Further development could also investigate integration with external simulation tools, databases, machine learning runtimes, and network-management interfaces. These integrations could support larger-scale experiments, persistent telemetry storage, and the evaluation of more advanced network-control strategies. However, these capabilities represent potential extensions and should not be interpreted as currently implemented features.

In conclusion, the proposed framework establishes a modular foundation for investigating digital twin-based network monitoring, routing, and operational decision support for 6G-oriented environments. Its combination of simulation, resource-aware routing, performance analytics, state snapshots, and rule-based recommendations provides a basis for controlled experimentation and future development. Further validation,

quantitative benchmarking, and the careful integration of predictive models are necessary to determine its effectiveness and scalability under increasingly complex network conditions.

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